International Journal of Scientific Engineering and Technology ISSN:2277-1581
Volume No.5 Issue No.6, pp: 379-382 01 July 2016

# MRI Image Retrieval System By Using CWT and Support Vector Machines

**Pritam Shivajirao Ambadkar, Prof. Devendra .G. Ingale**
Dept. of Electronics &Telecom Engineering, JSPMs, Jayawantrao Sawant College of Engineering,
Affiliated to Savitribai Phule Pune University, India
a.preet87@gmail.com, ingale.dg2@gmail.com

***Abstract-This paper introduces a image recovery system taking into account double tree complex wavelet change (CWT) and support vector machines (SVM). There are two traits of picture recovery framework. To begin with, pictures that a client needs through inquiry picture are like a gathering of pictures with the same origination. Second, there exists non-straight relationship between highlight vectors of various pictures. Standard DWT (Discrete Wavelet Transform), being non-excess, is an intense device for some non-stationary Signal Handling applications, however it experiences three major limitations;1) shift affectability, 2) poor directionality, and 3) nonappearance of stage data. To lessen these confinements, Complex Wavelet Change (CWT). The starting inspiration driving the improvement of CWT was to profit unequivocally both size and stage data. At the main level, for low level component extraction, the double tree complex wavelet change will be utilized for both surface and shading based elements. At the second level, to separate semantic ideas, we will assemble restorative pictures with the utilization of one against all bolster vector machines. We are utilized here Euclidean separation for to quantify the closeness between database elements and inquiry highlights. Additionally we can utilize a relationship based separation metric for correlation of SVM separations vectors. The proposed approach has better recovery execution over the current straight element joining.***

***Keywords— Content Based Image Retrieval system, Dual Tree complex Wavelet Transform, Support Vector Machines .***

## I. Introduction

In the clinical routine of perusing and deciphering medicinal pictures, clinicians (i.e., radiologists) frequently allude to and contrast the comparative cases and checked indicative results in their choice making of recognizing and diagnosing suspicious infections. In any case, looking for and distinguishing the comparable reference cases (or pictures) from the huge and assorted clinical databases is a very troublesome errand. The development in advanced advances for registering, systems administration, and database capacity has empowered the mechanized looking for clinically important and outwardly comparative restorative examinations (cases) to the questioned case from the huge picture databases. There are two sorts of general methodologies in restorative picture recovery to be specific, the content (or semantic) based picture recovery (TBIR) and the substance based picture recovery (CBIR). Highlights from inquiry picture are removed by the same indexing instrument. At that point these question picture elements are coordinated with highlight database utilizing a likeness metric and, at long last, comparative pictures are recovered. A larger part of indexing strategies depend on pixel area elements, for example, shading, composition and shape. Some recurrence space strategies incorporate wavelet area highlights, Gabor change and Fourier space highlights for highlight extraction. Extensive study of existing CBIR methods can be found in [9, 11]. Composition alludes to the visual examples that have properties of homogeneity not coming about because of vicinity of standout shading or power. It is an inherent property of for all intents and purposes all surfaces, including mists, trees, blocks, hairs, fabric, and so on. It contains critical data about the auxiliary course of action of surfaces and their relationship to the encompassing environment. Kingsbury [16] proposed another complex wavelet change which permits quick registering Gabor like wavelets. Dwindle and Kingsbury [14] in their paper have indicated how one can utilize this new change to accelerate and improve the picture. Kokare et al. [6] have proposed far better augmentation of this work. We can improve the surface extraction abilities of CWT for shading picture recovery. We can accomplish practically the same exactness for shading picture recovery too.

These properties of CWT have propelled us to utilize it as highlight extraction for our proposed framework. There are numerous example coordinating and machine learning devices and strategies for bunching and order of directly distinguishable and non-detachable information. Bolster vector machine (SVM) is a generally new classifier and it depends on solid establishments from the wide range of factual learning theory [10].

## II. Material and Methodology

There are two techniques are used in this project
1. Dual tree complex wavelet transform
2. Support vector machines

### 1. Dual Tree Complex Wavelet Transform

Wavelets are being used in many different areas like signal denoising, image, audio and video compression, image smoothing and differential equation solution are active research topics. Wavelets offer some advantages as a tool for image processing, such as the multi resolution

 ISSN:2277-1581
01 July 2016

formulation, which allows the reduction of computational complexity. Kingsbury's [16] dual tree complex wavelet transform (CWT) is an enhancement to the discrete wavelet transform (DWT), with important additional properties. The main advantages, as compared to the DWT, are that the complex wavelets are approximately shift invariant and that the complex wavelets have separate sub-bands for positive and negative orientations. Conventional separable real wavelets only have sub-bands for three different orientations at each level, and cannot distinguish between lines at 45◦ and −45◦ respectively. The complex wavelet transform attains these properties by replacing the tree structure of the conventional wavelet transform with a dual tree. At each scale one tree produces the real part of the complex wavelet coefficients, while the other one produces the imaginary parts. A complex-valued wavelet ψ (t) can be obtained as:

$$\psi (t) = \psi h (t) + j\psi g (t)$$

Where ψh (t) and ψg (t) are both real valued wavelets. CWT like Gabor transform has six orientations at each of four scales. The main advantage, as compared to the Gabor transform, is speed of computation. It has a redundancy of only 4 in 2-dimensions and so the post- processing stages (of calculating mean and standard deviations) are also faster as it has less redundancy than the Gabor wavelets. One can see more details related to orientation and scales. Each row represents one scale and the columns represent angles within that scale.

The four scale decomposed image by using DWT then that provide three directional filter that angles are 0, 45, 90 degree. While decomposed by using DTCWT then provide six directional filters that angles are ±15, ±45, and ±75 degree.

## 2. SUPPORT VECTOR MACHINES:-

There are many pattern matching and machine learning tools and techniques for clustering and classification of linearly separable and non separable data. Support vector machine (SVM) is a relatively new classifier and it is based on strong foundations from the broad area of statistical learning theory [12]. It is being used in many application areas such as character recognition, image classification, bioinformatics, face detection, financial time series prediction etc.

SVM offers many advantages over other classification methods such as neural networks. Support vector machines have many advantages in comparison with other classifiers:

1.There are computationally very efficient as compared with other classifiers, especially neural networks.

2.They work well, even with high dimensional data. And with less number of training data.

3.They attempt to minimize test error rather than training error. • They are very robust against noisy data.

4.The curse of dimensionality and over fitting problems does not occur during classification.

Fundamentally, SVM is a binary classifier, but can be extended for multi-class problems as well. The task of binary classification can be represented as having, (Xi, Yi) pairs of data. Where Xi∃Xp, a p dimensional input space and Yi∃ [−1, 1] for both the output classes. SVM finds the linear classification function g(x) = W.X +b, which corresponds to a separating hyper plane W. X+b = 0, where w and b are slope and intersection SVM usually incorporates kernel functions for mapping of non-linearly separable input space to a higher dimension linearly separable space. Many kernel functions exist such as radial bases functions (RBF), Gaussian, linear, sigmoid etc. Different options exist to extend SVM for multi class cases; these include one against all, one against one and all at once.

## I. PROPOSED SYSTEM

In the proposed SVMBIR framework in detail. Figure shows the main components of the proposed system and the control flows among them. The following steps show the detail of our proposed algorithm:

Step 1: Features are extracted from each picture using complex wavelet transform. So we got 24 real and 24 imaginary information sub-bands, and 2 real and 2 imaginary approximation sub-bands. We got 26 sub-bands. To calculate the features we measured the mean and standard deviation of the magnitude of the transform coefficients in each of 26 sub-bands. These features were stored in feature database for later comparison.

Step 2: From each class of pictures included in the image database some typical images (K) were grabbed for training of support vector machine for that class. Selection of these training images can be done randomly or from a sequence. In our experiments we used first K pictures for training. We used one opposite all training method as it is the best when one needs good speed and reliable performance. This is done using train's svm function of LSSVM. We used 'RBF' as kernel function for training of support vector machines. Optimal parameter selection is always a bottleneck of support vector machines. LSSVM provides a function tunnels svm which can be used for estimation of optimal parameters. We used grid search approach for searching optimal parameters.

Step 3: The gap of each image included in the database from each trained SVM is calculated. This is done using similar SVM math's expression of LSSVM. Each of this gap is grouped in the form of distance vectors. This distance vector will store gap of every image from each support vector machine. Finally, we add all these distance vectors in distance vectors database.

Steps 1 – 3 are done offline and after these steps our system is ready to process the user problem.

International Journal of Scientific Engineering and Technology ISSN:2277-1581
Volume No.5 Issue No.6, pp: 379-382 01 July 2016

Step 4: When the user gives the query to system, features from the query image are extracted. Using this feature vector of query image distance vector of query image is measured.

Step 5: Query image feature vector is matched with all the feature vectors included in the respective class in database. The Euclidean distance metric can be used for this comparison

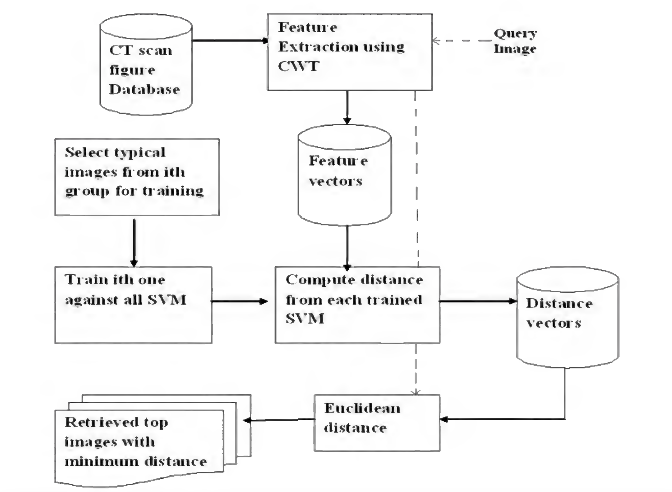


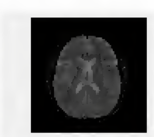

Fig 1. The structure of the proposed system

## III. Results and Tables

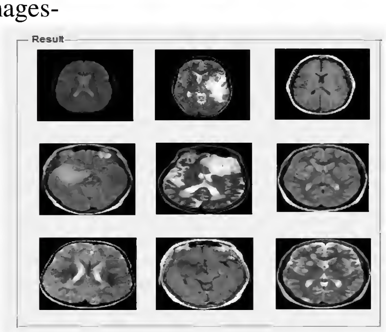
There are 6 different classes of MRI or CT scan images are used .Total 90 images stored in the database. from this classes one image is shown below in fig.

A. Expected Result:-There are total 90 images and six classes of Heart, brain, hands, legs, chest

1. Original Image-



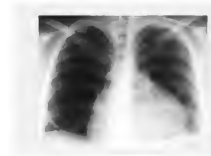
.Retrieve Images-




.

Fig.2 Retrieved results of SVM for Query image (01.jpg) from class1

2.Original Image-



Retrieve Image

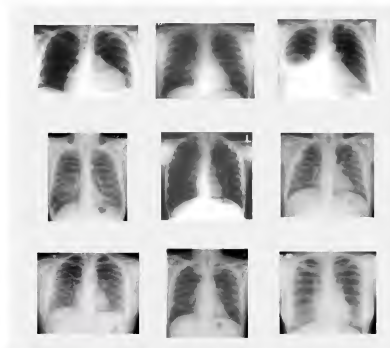
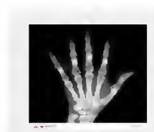


Fig.3 Retrieved results of SVM for Query image (070.jpg) from class5

3.Original Image-



Retrieve Image

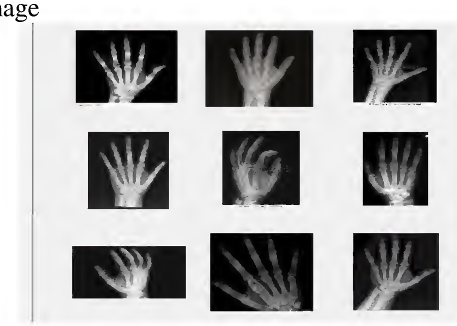


Fig..3 Retrieved results of SVM for Query image (041.jpg) from class1

| Class/ No of images | Query image | Method of feature extraction | No of image retrieved | Relevant image retrieved | Precision and retrieved efficiency | Error rate |
|---|---|---|---|---|---|---|
| Class 1 (Brain images) 1 to 15 | 01.jpg | DWT | 18 | 17 | 0.95 | 0.05 |
| | | CWT | 20 | 20 | 1 | 0 |
| | | CWT & SVM | 4 | 4 | 1 | 0 |
| Class 2 (Heart images) 15 to 30 | 017.jpg | DWT | 32 | 14 | 0.44 | 0.56 |
| | | CWT | 22 | 13 | 0.59 | 0.41 |
| | | CWT & SVM | 10 | 7 | 0.7 | 0.3 |
| Class 3 (Hand images) 31 to 45 | 041.jpg | DWT | 50 | 5 | 0.1 | 0.9 |
| | | CWT | 15 | 12 | 0.8 | 0.2 |
| | | CWT & SVM | 16 | 11 | 0.69 | 0.31 |
| Class 4 (Whole | 051.jpg | DWT | 20 | 16 | 0.8 | 0.2 |
| | | CWT | 17 | 05 | 0.29 | 0.71 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Heart images) 46 to 60 | | CWT & SVM | 16 | 9 | 0.56 | 0.44 |
| Class 5 (Chest images) 61 to 75 | 070.jpg | DWT | 32 | 15 | 0.47 | 0.53 |
| | | CWT | 21 | 8 | 0.38 | 0.62 |
| | | CWT & SVM | 9 | 5 | 0.55 | 0.45 |
| Class 1 (legs images) 76to 90 | 081.jpg | DWT | 52 | 11 | 0.21 | 0.79 |
| | | CWT | 17 | 05 | 0.29 | 0.71 |
| | | CWT & SVM | 4 | 3 | 0.75 | 0.25 |

**Table (1): Performance of retrieval system compared using Precision and Error rate**

## IV. CONCLUSION

The proposed system is based on the observation that the images users need are often similar to a set of images with the same conception instead of one query image and the assumption that there is a nonlinear relationship between other features. We used complex wavelet transform for feature extraction due directionality property. SVM is used for classification. CWT with SVM retrieval framework gives better Precision and minimum Error rate.

### ACKNOWLEDGMENT

We might want to thank the analysts and also distributers for making their assets accessible. We additionally appreciative to commentator for their significant recommendations furthermore thank the school powers for giving the obliged base and backing.

## REFERENCES

i. Sanchita Pange and Sunita Lokhande *"Image retrieval system by using CWT and support vector machines"* An international journal SIPIJVol.3, No.3(2012)

ii. Xiang-Yang Wang a,b, Yong-Jian Yu a, Hong-Ying Yang, "*An effective image retrieval scheme using color, texture and shape features"*, Journal Computer Standards & Interfaces archive Volume 33 Issue 1, January, 2011.

iii. Jagadeesh Pujari , Pushpalatha S.N, Padmashree D.Desai, "*Content-Based Image Retrieval using Color and Shape Descriptors*", Signal and Image Processing (ICSIP), 2010 International Conference on, pp: 239 – 242

iv. Jagadeesh Pujari , Pushpalatha S.N, Padmashree D.Desai, "*Content-Based Image Retrieval using Color and Shape Descriptors*", Signal and Image Processing (ICSIP), 2010 International Conference on, pp: 239 – 242

v. Yi Liu and Yuan F. Zheng,"*One-Against-All Multi-Class SVM Classification Using Reliability Measures"*

vi. M. KOKARE, P. K. BISWAS, B. N. CHATTERJI, *Texture Image Retrieval Using New Rotated Complex Wavelet* Filters. SMC-B, 35(6) (2005), 1168–1178.

vii. SAP standard for System Monitoring White paper by SAP Press

viii. Alexandros Karatzoglou, David Meyer, Kurt Hornik," *Support Vector Machines in R"*

ix. Dengsheng Zhang and Guojun Lu," *similarity of measurement for image retrieval"*, IEEE 2003

x. R. C. VELTKAMP, M. TANASE, *Content-based Image Retrieval Systems*: A Survey. UU-CS-2000-34, Department of Computer Science, Utretch University, October 2002.

xi. J. A. K. SUYKENS, T. VAN GESTEL, J. DE BRABANTER B. DE MOOR, J.VANDEWALLE, *Least Squares Support Vector Machines*. World Scientific, Singapore, 2002.

xii. B.Ramamurthy, K.R.Chandran, *"Cbmir: Shape-Based Image Retrieval Using Canny Edge Detection And K-Means Clustering Algorithms For Medical Images",* International Journal of Engineering Science and Technology (IJEST) Mar 2011.

xiii. [24] Jing Zhang, Gui-li Li, Seok-wun He, *"Texture-Based Image Retrieval by Edge Detection Matching GLCM",* The 10th IEEE International Conference on High Performance Computing and Communications, Sept. 2008, pp: 782 – 786.

xiv. R. PETER, N. KINGSBURY, *Complex Wavelets Features for Fast Texture Image retrieval*. Proc IEEE Int. Conf. on Image Processing, (1999), 25–28.

xv. C. J. C. BURGES, *A Tutorial on Support Vector Machines for Pattern Recognition. Data Mining and Knowledge* Discovery, 2(2) (1998), 955–974.

xvi. N. G. KINGSBURY, The Dual Tree Complex Wavelet Transform: A New Efficient Tool for Image Restoration and Enhancement. Proc. European Signal Processing Conf., (1998).

xvii. Jieping Ye, Tao Xiong,"SVM versus Least Squares SVM"